Chapter 7: Developing Climate-Informed State-and-Transition Models

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Chapter Summary

Land managers and others need ways to understand the potential effects of climate change on local vegetation types and how management activities might be impacted by climate change. To date, climate change impact models have not included localized vegetation communities or the integrated effects of vegetation development dynamics, natural disturbances, and management activities. We developed methods to link a dynamic global vegetation model to local state-and-transition models. Our methods allow examination of how climate change effects might play out in localized areas given a combination of vegetation dynamics, natural disturbances, and management actions. Initial results for the eastern Cascades of central Oregon suggest that ponderosa pine forests are likely to remain the dominant forest vegetation type while moist and subalpine forests decline. Sagebrush shrublands will likely also remain the dominant arid land vegetation type, but could undergo substantial fluctuations and begin to give way to shrublands dominated by warm-season species.

Our methods allow examination of how climate change effects might play out in localized areas given a combination of vegetation dynamics, natural disturbances, and management actions.

Introduction

Resource planners and managers are often inundated with information on climate change and potential corresponding trends in wildfire, drought, insect outbreaks, and silvicultural treatment effects. These factors are frequently discussed independently of each other without considering how one may affect the other. Incorporating and utilizing various pieces of information can be difficult, because information on these factors is often generated at different spatial and temporal scales with both known and unknown uncertainties.

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One source of confusion is the interpretation of projections from general circulation models (also referred to as global climate models [GCMs]). The GCMs reflect the current state of knowledge and understanding of how the planet's climate system works. However, our climate system is very complex, and different GCMs incorporate different assumptions about the physical drivers of the Earth's climate, resulting in varied projections of future temperature and precipitation. It is difficult for managers and planners to translate these various climate projections into plausible scenarios of future ecosystem change and to develop robust adaptation strategies, because there are many models and assumptions about the current understanding of local feedbacks.

Downscaling climate projections from different GCMs to drive projections of vegetation growth, and corresponding changes in drought and wildfire, is a necessary step to begin to make GCM results useful to natural resource managers and planners. Dynamic global vegetation models (DGVMs) such as MC1 (Bachelet et al. 2001, Daly et al. 2000) have been developed to integrate climate information and grow vegetation through time by simulating fundamental ecological processes like carbon and water uptake and losses, and competition for light, water, and nutrients. The required climate information to run the DGVMs, including minimum and maximum temperatures, precipitation, and vapor pressure deficit, is provided by interpolated climate observations for both the historical period and climate scenarios for the future. However, because DGVMs simulate changes in broad functional vegetation types, the output is not readily usable by managers and planners and is often not appropriately scaled to address many management and planning questions. Moreover, many DGVMs omit important drivers of vegetation dynamics, such as species-specific fire tolerance and human-driven landscape change, and generalize processes such as plant competition and succession.

State-and-transition models (STMs) incorporate effects of succession, management, and disturbance on relatively fine-scale vegetation composition (i.e., communities) and structure. The STMs have been used for many different types of landscape-scale assessments (e.g., Arbaugh et al. 2000; Forbis et al. 2006; Hemstrom et al. 2001, 2007; Merzenich et al. 2003; Merzenich and Frid 2005; Weisz et al. 2009). However, most STMs do not currently incorporate potential effects of climate change. Because STMs do not consider a changing climate, site potential in these models currently does not change through time, resulting in static potential vegetation for any modeled location. Fire frequency and severity is also currently unchanged through time in STMs. Integrating vegetation models such as MC1 with STMs would help make the information provided by MC1 about climate change effects on vegetation and disturbance regimes more useful for natural resource managers.

The Integrated Landscape Assessment Project (ILAP) was a $6 million investment funded by the American Recovery and Reinvestment Act to inform watershed-level planning, assessment, and prioritization of land management actions across wildlands in Arizona, New Mexico, Oregon, and Washington. The ILAP has partnered with many organizations across the Western United States, including state and federal agencies, universities, nonprofit organizations, and tribes. As part of ILAP, we used the MC1 DGVM to inform changes in vegetation potential and changing trends in fire probabilities in a suite of local STMs. This process was used in two focus areas (central Oregon and eastern Arizona). The outcome of our process was a collection of climate-informed STMs, which are connected to each other, allowing climate-driven shifts in potential vegetation to occur. These climate-informed STMs can be used to weigh potential benefits or tradeoffs associated with alternative land management approaches in mid- to broad-scale landscapes. In this chapter, we describe the methods we used to develop climate-informed STMs in central Oregon. Although the approach was nearly identical in eastern Arizona, we use central Oregon here to illustrate the process and results that can be produced.

Climate-informed STMs can be used to weigh potential benefits or tradeoffs associated with alternative land management approaches in mid- to broad-scale landscapes.

Study Area

The study area is a landscape of forested and arid vegetation that covers approximately 1 023 808 ha in eastern central Oregon (fig. 7.1). The study area lies along a sharp rain shadow generated by the north-south trending Cascade Mountain range. Elevations vary from about 1200 m to above 2400 m. The climate is transitional between moist, maritime conditions west of the Cascade crest and continental conditions to the east. Annual precipitation varies from over 200 cm along the Cascade crest to less than 35 cm along lower timberline, and 25 cm at the lowest elevations in shrub-steppe environments. Most of the precipitation falls as rain and snow during the winter months, with snowpacks of more than 2 m common in upper elevations. Summers are warm and dry, often with several weeks of very low or no precipitation and warmest temperatures at lower elevations exceeding 30 ˚C. Thunder storms and lightning commonly occur from April through September.

A variety of mostly coniferous tree species dominate the forested lands. We defined seven potential vegetation classes (PVCs) by aggregating plant associations described by Simpson (2007), Johnson and Simon (1987), Johnson and Clausnitzer (1992), and Johnson and Swanson (2005), and added an additional eighth type that the DGVM indicates might be common in the future:

1. Temperate needle-leaved forests. Ponderosa pine is the dominant early early-seral tree species at the lowest forested elevations. Dry forests containing a mix of ponderosa pine, Douglas-fir, and grand fir are abundant at middle elevations.

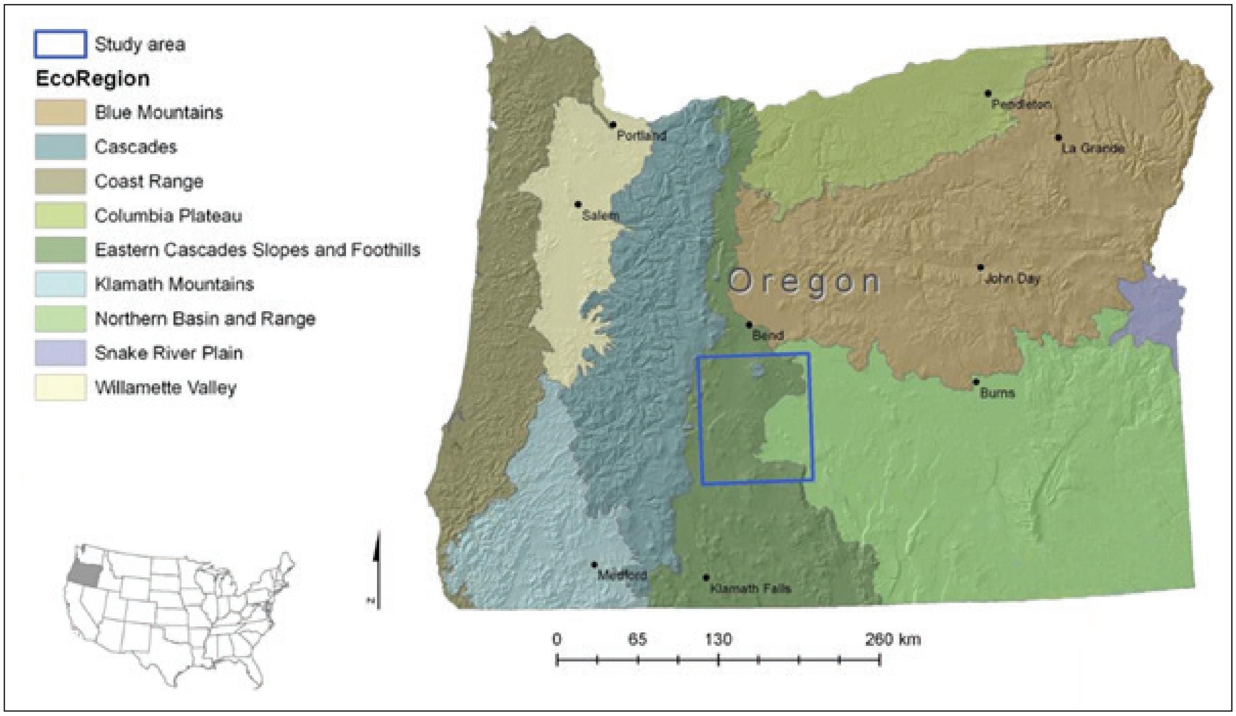

Figure 7.1—Study area and ecological (Omernik level III) regions in central Oregon.

2. Cool needle-leaved forests. Upper montane forests are a variable mixture of conifer species, including Douglas-fir, white fir, Shasta red fir, ponderosa pine, and other species. In very moist environments, several conifers more common to the western Cascades may be abundant, including Pacific silver fir, western hemlock, and western redcedar.
3. Subalpine forests. Mountain hemlock dominates upper elevation cold forests in moist environments, while whitebark pine, Engelmann spruce, and subalpine fir dominate in drier cold forests. Lodgepole pine is common in disturbed, especially burned, areas at upper elevations.
4. Temperate needle-leaved woodland. Western juniper and mountain big sagebrush, with several other shrubs, grasses, and forbs, occupy mid- to upper elevation woodlands and shrublands that do not currently support forests.
5. Temperate shrubland. Much of the lower elevation, warm, dry temperate shrubland is dominated by Wyoming big sagebrush communities that have little or no potential for invasion by western juniper. Cheatgrass is a prevalent invasive annual grass in many Wyoming big sagebrush types.
6. Xeromorphic shrubland. Salt desert shrub communities with greasewood, saltbush, and Wyoming big sagebrush are of somewhat limited distribution in low-elevation areas, particularly those with saline soils. Cheatgrass is often invasive in these shrublands.

7. Temperate grassland. Various bunchgrass-dominated grasslands, often including Idaho fescue and bluebunch wheatgrass, form scattered grasslands dominated by cool-season (i.e., C3) species. Cheatgrass can be invasive in these grasslands.
8. Warm-season grassland. Warm-season grasslands do not occur to any significant extent in the study area at present, but do occur in warmer areas to the south. We included a warm-season grassland potential vegetation type because MC1 model projections indicated they might occur in our area in the future.

Methods

MC1 Modeling

MC1 (Bachelet et al. 2001) is a DGVM that reads soil and monthly climate data, and calls interacting modules that simulate biogeography, biogeochemistry, and fire disturbance. The biogeography module simulates life form or plant functional type mixtures, classifying them into PVCs; the biogeochemistry module simulates fluxes and pools of carbon, nitrogen, and water through ecosystems; and the fire module simulates natural fire disturbance. Each module is described in the following paragraphs. MC1 routinely generates century-long, regional-scale simulations (e.g., Bachelet et al. 2000, 2003, 2005; Lenihan et al. 2008).

The MC1 biogeography module simulates mixtures of needle-leaved or broad-leaved evergreen and deciduous trees, as well as temperate (C3) and warm-season (C4) grasses. The tree life form mixture is determined at each annual time-step as a function of annual minimum temperature and growing season precipitation. The temperate/warm-season grass mixture is determined by reference to their relative potential productivity during the three warmest consecutive months. Tree and grass life form mixtures, their biomass levels as simulated by the biogeochemistry module, and growing degree-day sums are used to determine which of several dozen possible PVCs occurs in each simulated grid cell each year (grid cell size was 800 m in this study). Shrubs are simulated as short-stature trees.

The MC1 biogeochemistry module is a modified version of the CENTURY model (Parton et al.1993), which simulates plant growth, organic matter decomposition, and the movement of water and nutrients through the ecosystem. Plant growth is determined by empirical functions of temperature, moisture, and nutrient availability. In this model, plant growth was assumed not to be limited by nutrient availability. The direct effect of an increase in atmospheric carbon dioxide is simulated using a beta factor (Friedlingstein et al.1995) that increases maximum potential productivity and reduces the moisture constraint on productivity. Grasses compete with woody plants for soil moisture and nutrients in the upper soil layers, where both are rooted, while the deeper rooted woody plants have sole access to resources in deeper layers. The growth of grasses may be limited by reduced light levels in the shade cast by woody plants. The values of model parameters that control woody plant and grass growth are adjusted with shifts in the life form mixture determined annually by the biogeography module.

The MC1 fire module simulates the occurrence, behavior, and effects of fire. The module simulates the behavior of a fire event in terms of the potential rate of fire spread, fireline intensity, and the transition from surface to crown fire (Cohen and Deeming 1985, Rothermel 1972, van Wagner 1993). Several measurements of the fuel bed are required for simulating fire behavior, and they are estimated by the fire module using information provided by the other two MC1 modules. The current life form mixture is used to select factors that allocate live and dead biomass into different classes of live and dead fuels. The moisture content of the two live fuel classes (grasses and leaves/twigs of woody plants) is derived from soil moisture provided by the biogeochemical module. Dead fuel moisture content is estimated from climatic inputs to MC1 using different functions for each of four dead fuel size-classes (Cohen and Deeming 1985).

Fire events are triggered in the model when the fine fuel moisture code (FFMC) and the buildup index (BUI) simultaneously exceed prescribed thresholds. The FFMC is a numerical rating of the relative ease of ignition and flammability, used in the Canadian Forest Fire Danger Rating System. The BUI is a number that reflects the combined cumulative effects of daily drying and precipitation in fuels, part of the 1964 National Fire Danger Rating System in the U.S. Sources of ignition (e.g., lightning or anthropogenic) are assumed to be always available. Area burned is not simulated explicitly as fire spread within a given cell. Instead, the fraction of a cell burned by a fire event is estimated as a function of set minimum and maximum fire return intervals for the dynamically simulated PVC and the number of years since the last simulated fire event.

The fire effects simulated by the model include the mortality or consumption of vegetation carbon, which is removed from (or transferred to) the appropriate carbon pools in the biogeochemistry module. Live carbon mortality and consumption are simulated as a function of fireline intensity and tree canopy structure (Peterson and Ryan 1986). Dead biomass consumption is simulated using functions of fuel moisture that are fuel class specific (Prichard et al. 2005).

Climate Data—

Climate data sets required for running the MC1 model consisted of monthly values of four variables: precipitation, the monthly means of diurnal extreme temperatures (minimum and maximum), and a measure of atmospheric water content. We used the Parameter-elevation Relationships on Independent Slopes Model (PRISM) climate data set at 30 arc-second spatial grain for the historical period (Daly et al. 2008). This data set contains monthly data for the years 1895 to 2008, for the conterminous United States on a 30 arc-second grid (about 800 m grain). PRISM estimates spatial means of temperature and precipitation for grid cells based on records from nearby weather stations, assigning weights to the station data according to the similarity of the station location to the grid cell location. PRISM, although not the only source for gridded historical climate data for the United States, is well established and has been widely used (Daly et al.1994, Guentchev et al. 2010).

Future climate projections from GCMs included in the Intergovernmental Panel on Climate Change (IPCC) fourth assessment report (Solomon et al. 2007) were used to drive MC1 projections for the 21st century. In this respect, our study is similar to a number of other studies using MC1 at various scales on a variety of landscapes (Bachelet et al. 2008, Conklin 2009, Gonzalez et al. 2010, Lenihan et al. 2008, Rogers 2011). We obtained complete time series of the four necessary climate variables from the data repository at Lawrence Livermore Laboratories produced by the Hadley CM3 (Gordon et al. 2000), MIROC 3.2 medres (Hasumi and Emori 2004), and CSIRO Mk3 (Gordon et al. 2002) GCMs (hereafter Hadley, MIROC, and CSIRO, respectively) for the IPCC Special Report on Emissions Scenarios (SRES) A2 emissions scenario (Nakićenović and Swart 2000). For the future 2070-2099 period, CSIRO projects a relatively cool and wet U.S. Pacific Northwest (+2.6 °C and +176 mm mean annual precipitation), MIROC projects a relatively hot and wet U.S. Pacific Northwest (+4.2 °C and +82 mm mean annual precipitation), and Hadley projects a relatively hot and dry U.S. Pacific Northwest (+4.2 °C and −78 mm mean annual precipitation) (Rogers et al. 2011). For all three GCMs, temperature increases are generally greater in summer than in winter, while precipitation increases in winter and decreases for summer (Rogers et al. 2011). Thus, the seasonality in temperature and precipitation that characterized the Pacific Northwest historically is increased (i.e., there is a greater difference in temperature and precipitation between seasons) in future projections by all three GCMs.

The spatial grids used by the Hadley, MIROC, and CSIRO GCMs are coarse (1.9 x 1.9 degrees for CSIRO, 2.8 x 2.8 degrees for MIROC, and 2.5 x 3.75 degrees for Hadley). We down-scaled the coarse grid GCM data to a 30 arc-second grid using a “delta” or “anomaly” method (Fowler et al. 2007). We first calculated a historical climate baseline (mean values for each month) for 1971-2000, our reference period, using PRISM data. We also calculated a coarse-scale historical baseline for the same reference period using the GCM projections. Secondly, for each month of each year of the future period, we calculated the difference (for temperature and vapor pressure) between or the ratio (for precipitation), of the future value and the reference historical baseline climate (the “deltas”). We then estimated the values of the deltas on the fine (30 arc-second) grid using bilinear interpolation between deltas from the coarse GCM grid. Finally, we calculated the fine grid climate values for each month of each year of the future period using the PRISM historical baseline modified by the fine-scale deltas. Difference deltas were added to the baseline, while ratio deltas were multiplied with the baseline.

State-and-Transition Models

We used a set of STMs that included both previously developed models that were modified and standardized in ILAP, and some new models built for ILAP (chapter 2). The STMs divide vegetation into state classes (boxes), representing combinations of cover type and structure stage within different biophysical environments (potential vegetation types). Boxes are linked by transitions (arrows) that represent natural disturbances, management actions, or vegetation growth and development. This approach builds on methods that represent vegetation development as a set of transition probabilities among various vegetative state classes (within, but not between biophysical environments; e.g., Hann et al.1997, Hemstrom et al. 2007, Keane et al.1996, Laycock 1991, Westoby et al.1989). For example, grass/forb lands might become dominated by small trees and shrubs after a period of time or might remain as grass/forb communities following wildfire. Our STMs include major natural disturbances, such as wildfire (low-severity [<25 percent canopy mortality], mixed-severity [25 to 75 percent canopy mortality], and high-severity [>75 percent canopy mortality]), insect outbreaks, wind disturbance, drought mortality, and others as appropriate to individual ecological systems. Wildfire probabilities in base STMs came from an analysis of empirical wildfire data for the 1984-2008 time period (Monitoring Trends in Burn Severity [MTBS]; Eidenshink et al. 2007; www.mtbs.gov) in the Oregon East Cascades modeling zone (chapter 2). The STMs were developed in the Vegetation Development Dynamics Tool (VDDT) framework, version 6.0.25, (ESSA Technologies Ltd. 2007) and run in the Path modeling platform, version 3.0.4 (Apex Resource Management Solutions 2012, Daniel and Frid 2012).

With the STM approach, a given area can transition from one state class to another within a potential vegetation type with growth, succession, natural disturbance, or management. However, the environmental conditions, and thus site potential, of an area do not change with time. For example, an area classified as having ponderosa pine potential cannot become a juniper woodland over time with drought. However, by adding climate information from the MC1 DGVM, we are able to simulate changes in the distribution of vegetation types over time, allowing us to create more realistic projections of future conditions under changing climate.

Vegetation maps—
We used a set of potential and current vegetation maps as spatial inputs for ILAP (chapter 2). Previously developed current and potential vegetation maps were used for portions of the four-state study area, including most of the forests in Oregon and Washington (with the exception of southeastern Oregon). These maps were developed by the U.S. Department of Agriculture, Forest Service Landscape Ecology Monitoring Mapping and Analysis team (http://www.fsl.orst.edu/lemma/splash.php). However, in most other regions of the study area, existing maps contained insufficient detail or were not sufficiently accurate to inform the STMs for ILAP. Where existing maps were insufficient to initialize the STMs (arid lands in Oregon and Washington and all lands in Arizona and New Mexico), ILAP built new maps using imputation modeling techniques (Crookston and Finley 2008, Ohmann and Gregory 2002). For potential vegetation maps, pixels were essentially assigned the plant association identified in inventory plots as a statistical function of grids of environmental variables, such as topography, slope, and climate. A rule set was developed that classified the plant association identified on each imputed pixel into one of the potential vegetation types. Current vegetation was also mapped using nearest neighbor imputation, but uses plot data (cover by species) instead of plant association and incorporates LANDSAT-TM imagery in addition to environmental variables to characterize current vegetation at the site. A rule-set was used to classify the current vegetation from each mapped pixel to one of our STM state classes. The resulting maps of potential and current vegetation were used to determine which STM to run in each geographic location and the initial starting conditions of the STMs (chapter 2).

Developing Climate-Informed State-and-Transition Models

We made several basic assumptions in connecting MC1 output with the STMs. First, we assumed that the general vegetation dynamics of major potential vegetation types near the study area adequately represented the general dynamics of similar vegetation in the future. We did not assume that the species mix in future vegetation types is static, only that the kinds of disturbances, successional patterns, and reactions to management in current plant communities sufficiently represent future communities well enough to be useful for examining vegetation and disturbance trends with climate change.

Second, we assumed that possible changes in vegetation potential from future climate change will be actuated by disturbances that return vegetation to early-seral conditions. Our supposition was that vegetation existing on a site uses resources and impedes development of altered plant communities unless a disturbance makes site resources available. We assumed that mixed- and high-severity wildfire, some management activities, some kinds of insect outbreaks, direct drought-related mortality in arid lands, and a few other major disturbances were of a sufficient magnitude to facilitate vegetation type change. We accounted for potential changes in fire regimes with climate change in our STMs through integration with MC1, but potential changes in insect disturbances with climate change are not incorporated in MC1 and thus were not incorporated in our STMs.

Third, we assumed that we could use a common, overlapping time period (1984–2008) to compare current vegetation and MC1 modeled vegetation to develop scaling factors that might allow us to attach trends and variation from MC1 projections to the vegetation potential and dynamics in the study area.

Step 1: Match local vegetation types to MC1 potential vegetation classes—
The connection between MC1 and STMs required cross-walking recent historical vegetation as mapped by MC1 to maps of ILAP potential vegetation types. MC1 produced an output grid for every simulation year showing the expected PVC for each grid cell (800 m). We compared the modeled MC1 PVC grid for the recent historical period (1984-2008) to the potential vegetation grid for the study area using a geographic information system (GIS) (fig. 7.2). The resulting GIS data were used to compute the area of ILAP potential vegetation types within each of the MC1 PVCs and for visual comparisons of PVC with potential vegetation locations for the recent historical period. The ILAP included more than two dozen potential vegetation types, substantially more spatial detail than that contained in the MC1 PVC maps. Consequently, we selected one ILAP potential vegetation type to represent each of the PVCs that occurred in MC1 simulations for either the recent historical or future time periods (table 7.1). We generally chose the most common potential vegetation to represent MC1 PVCs. For simplicity, we dropped any MC1 PVC that never exceeded 1 percent of the study area in either time period. This process resulted in seven potential vegetation types that we related to seven MC1 PVCs. In addition, MC1 simulated more than 1 percent of the study area in warm-season (i.e., C4) grasslands under some climate scenarios in the future. The map of potential vegetation from ILAP did not include any warm-season grasslands, so we added an eighth type that only occurred in future simulations. Our warm-season grassland STM was modified from a similar potential vegetation type that occurs in adjacent Nevada.

Step 2: Tune MC1 potential vegetation classes—
MC1 used a set of rules that assign combinations of biomass, carbon, climate factors, and other data to a PVC. We examined the rules and PVCs simulated for the historical period (1971–2000) to better understand how they related to other maps of historical vegetation (Kuchler 1964). We changed the interpretation of two PVCs

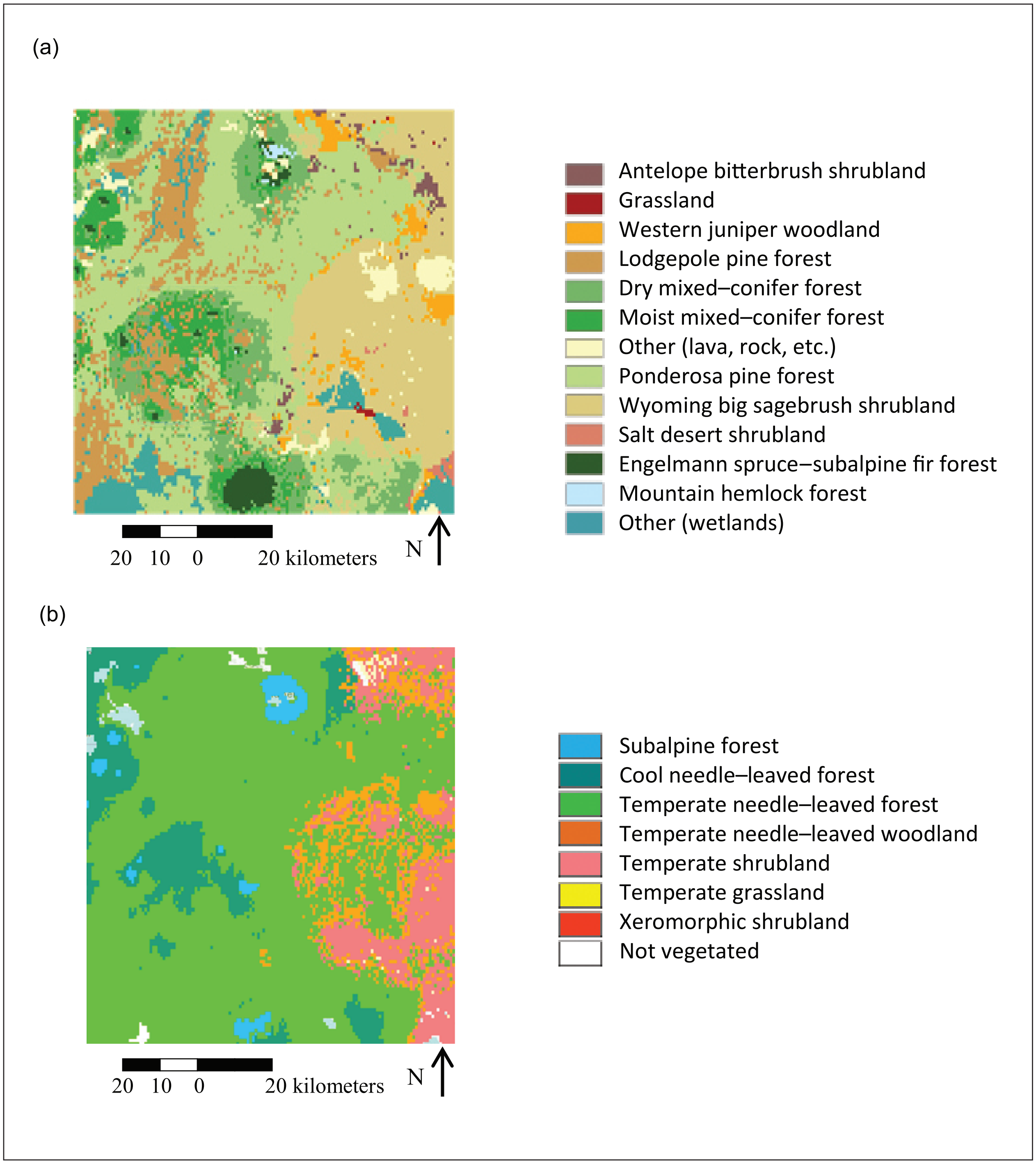

Figure 7.2—Potential vegetation types mapped from (a) imputation of inventory plots and (b) recent historical (1971–2000) vegetation simulated by MC1.

Table 7.1—MC1 potential vegetation classes and their corresponding potential vegetation types in the study area[a]

MC1 potential vegetation classes	State-and-transition model potential vegetation type	Mapped current extent	MC1 current extent
		Percent	
Subalpine forest	Mountain hemlock forests	2	2
Cool needle-leaved forest	Moist mixed conifer forests	11	4
Temperate needle-leaved forest	Ponderosa pine–lodgepole pine forests	59	67
Temperate needle-leaved woodland	Mountain big sagebrush–with juniper	14	6
Temperate shrubland	Wyoming big sagebrush	12	18
Xeromorphic shrubland	Salt desert shrub	2	<1
Temperate grassland	Bluebunch wheatgrass–Sandberg bluegrass grassland	<1	3
Warm-season grassland	Warm-season grassland	0	0

[a] The "Mapped current extent" of forested potential vegetation types was developed from the U.S. Department of Agriculture Forest Service's Landscape Ecology Monitoring Mapping and Analysis team (http://www.fsl.orst.edu/lemma/splash.php), and the maps of arid land potential vegetation types were developed as a part of the Integrated Landscape Assessment Project.

to better match maps of historical vegetation. MC1 simulated substantial areas of maritime needle-leaved forests in middle- and upper-elevation forested areas in the study area, where the historical vegetation map indicated cool white fir and moist mixed-conifer conditions. MC1 suggested that the diurnal temperature fluctuation in these areas was less than that in most inland forests. Rather than label these as maritime forests, we labeled them as cool and moist needle-leaved forests. Likewise, MC1 simulated some areas in very warm, dry environments as coniferous xeromorphic woodland. Comparisons to the historical vegetation map suggested they should be labeled xeromorphic shrubland instead.

Step 3: Run MC1 and summarize for future climate scenarios—
We ran MC1 for the three future climate scenarios using down-scaled (800-m grid) climate input data for the 2010 to 2100 time period. We analyzed the annual output from each scenario and developed a set of tables that depict the yearly total proportion of the landscape in each PVC, the yearly directional change in area among PVCs, and the yearly proportion of the landscape burned. Yearly directional change among PVCs was the pair-wise proportion of area moving from one PVC to another over the 1-year time step. The resulting tables, when combined with output from the historical run of MC1, allowed us to examine the historical and possible future PVC trends and wildfire trends for all the selected PVCs during the 1895 to 2100 time period.

Step 4: Construct a state-and-transition megamodel—
We developed an STM "mega-model" by combining all eight individual STMs representing the selected potential vegetation into one large, interconnected STM. MC1 output determined which climate change transitions among potential vegetation types to include in the STM megamodel, but we also had to determine when those changes were going to occur. Our assumption that climate change effects could be expressed only from early-seral vegetation conditions meant that climate change transitions connected early-seral state classes in STMs losing area to parallel early-seral state classes in STMs receiving area.

Step 5: Compute climate change and wildfire trends—
We identified PVC changes simulated by MC1 between 2010 and 2100 for three climate change scenarios (MIROC-A2, CSIRO-A2, and Hadley-A2). We then calculated the average annual probability for each of those changes by dividing the area in which the PVC change occurred each year by the total area of the study region, and averaging it across all years. Average annual probabilities for PVC changes were incorporated in STMs as transitions that led from postdisturbance and early-seral state classes of a source STM toward a different STM state class.

We assumed that these new climate change transitions would occur either following stand-replacing disturbances of any kind that affected any state class in the STMs or when vegetation was in an open condition. Essentially, change in vegetation potential could happen when a shift in vegetation potential was simulated by MC1 and when vegetation was in an open condition or when disturbance removed most of the current vegetation. We then computed the annual departure of PVC change from the overall mean change for each climate change transition. For each year simulated by MC1, a scalar indicated how much the PVC trend was above or below the long-term average trend. This method produced a set of trend multipliers for our STM that tracked the year-to-year changes in PVCs simulated by MC1. These trend multipliers were applied as annual multipliers to scale the proportional annual movement of area among the relevant state classes within and between the STMs.

In addition to vegetation type trends, MC1 projects wildfire dynamics into the future. We analyzed the wildfire trends from MC1 and applied them in similar fashion as trend multipliers to the wildfire transitions in our STM. Since our MC1 runs assumed no fire suppression, but the MTBS data were from a period with fire suppression (1984–2008), we could not use the MC1-derived probabilities directly. Instead, we used the overlap in wildfire data from the MTBS sampling period and the MC1 outputs for the 1984 to 2008 time period to develop a base relationship between MC1 proportion of cells burned to the average wildfire probabilities for the study area from MTBS data. We then scaled future wildfire probabilities in our STM according to trends from MC1.

The MTBS does not capture small fires (<405 ha) and may underestimate fire frequency. Thus, using the MTBS record could lead to relatively low estimates of fire area burned for the future. However, MC1 assumes that ignitions are not limiting. In other words, fire always occurs in a cell when fuel and weather conditions are in a certain range. Thus, MC1 may overestimate future fire area burned.

Step 6: Run and check state-and-transition megamodel—
The process of summarizing and computing climate change transitions from MC1 data was performed as a set of database and linked spreadsheet operations. Three individuals checked the databases and spreadsheets for errors. Once the STM megamodel was developed, we ran at least 10 simulation tests to check for logic errors and model sensitivity. Test simulations were carefully reviewed and the STM output compared to raw MC1 projections. We ran multiples of climate change trends, each ramping up climate change trends by two, four, and eight times. Similarly, we ran multiples of wildfire trends. We looked at figures of proportion of the landscape in different PVCs over time (e.g., fig. 7.3) to qualitatively assess model sensitivity. We found that the STM megamodel was highly sensitive to changes in climate change trends, but not as sensitive to changes in wildfire, especially in forested types. Increased fire frequency in several forest types merely reinforced development of open forests with large, fire-resistant trees (e.g., ponderosa pine). On the other hand, increased wildfire rates had larger effects in arid lands, where frequent wildfire favors increases in exotic annual grasses.

Results

Although we ran MC1 and our climate-informed STM for three future climate scenarios, we limit our results here to the MIROC-A2 scenario. We chose this scenario for illustration purposes because it is moderate in terms of temperature and precipitation change for the Pacific Northwest. In addition, although spatial results are possible with our coupled model process, we did not examine them for the purposes of this report, but plan to include them in forthcoming reports.

Historical Period Potential Vegetation and Wildfire—MC1 Simulation Results

Except for a short period in the early 1900s, temperate needle-leaved forest (TNF) occupied over half the study area for the entire historical period, and at present, TNF potential existed across 50 to 70 percent of the study area (fig. 7.3). This agreed reasonably well with our potential vegetation maps for the study area, in

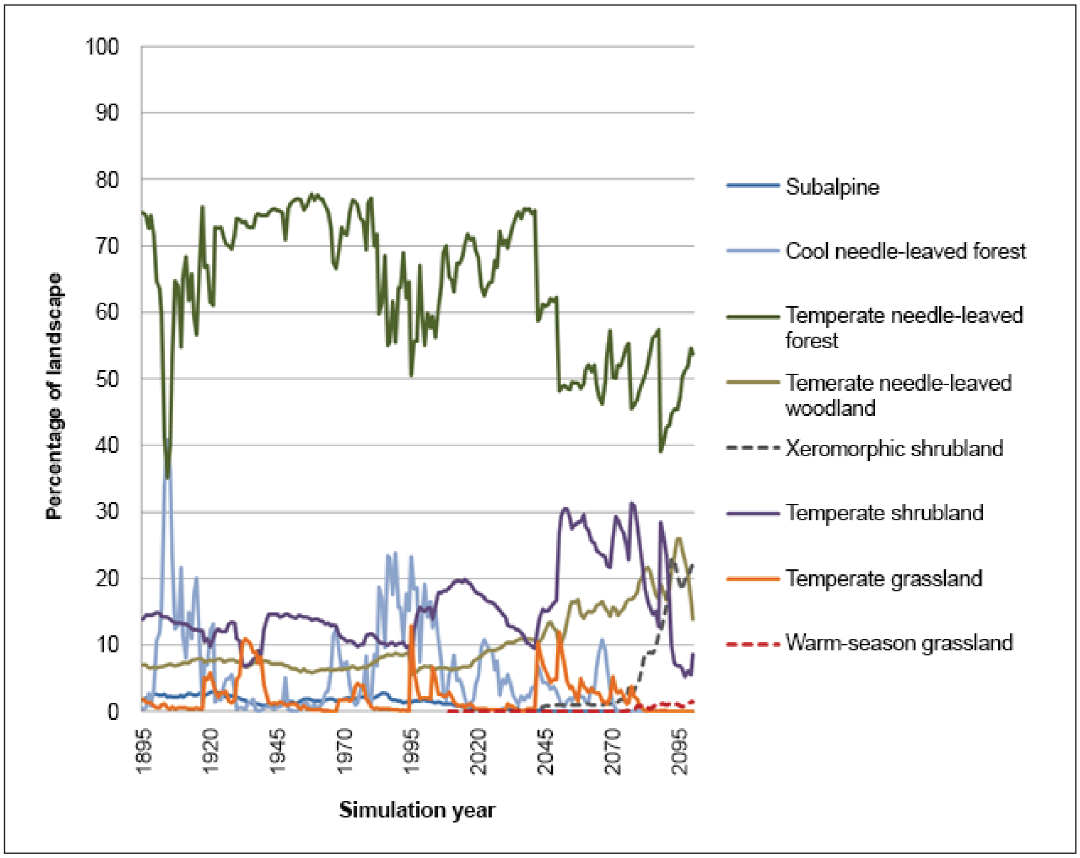

Figure 7.3—MC1 projections of annual extent of selected vegetation types for historical (1895–2008) and future (2009–2100) periods (using MIROC general circulation model climate projections under the A2 emissions scenario).

which the corresponding ponderosa pine/lodgepole pine forest type occupied about 59 percent of the landscape area. In addition to temperate needle-leaved forests, MC1 projected significant but variable amounts of cool needle-leaved forests and small amounts of subalpine forests. These also compared well with our estimates of current amounts. Temperate shrubland dominated arid lands in simulated historical conditions and generally occupied 10 to 15 percent of the landscape area. Temperate needle-leaved woodlands were also prominent, and there were minor amounts of temperate grasslands, as was the case in our current vegetation map. Our historical simulations did not show significant areas of xeromorphic shrublands or warm-season grasslands.

Overall, wildfire simulations from MC1 for the historical period (1895–2008) varied considerably from year to year, especially in arid lands (fig. 7.4). There were high fire years in the early 1930s and in the 1994 to 2008 period. Relatively less arid land burned in other years, and forested lands generally experienced little wildfire. The hot and wet MIROC-A2 scenario produced highly variable wildfire in arid lands, with spikes to over 80 percent of cells burned in 2041, 2049, 2069, 2087, and

2099. Wildfire also increased in forested lands under MIROC-A2, but amounts were much lower (<40 percent burned) compared to arid lands.

Future Vegetation Conditions—MC1 Simulation Results

Under the MC1 DGVM simulation results alone (without the STMs), temperate needle-leaved forests rose to >70 percent of the study area by 2039, and then dropped to 40 percent to 55 percent of the area until 2100 (fig. 7.3). Cool needle-leaved forests occupied between zero and 20 percent of the landscape, then area of climatically suitable habitat was nearly zero by 2075. Climatically suitable habitat for subalpine forests declined to nearly zero by 2020. Temperate shrublands were variable, initially declining somewhat from current conditions, then rising sharply to more than 25 percent of the area, and ultimately declining to <10 percent of the landscape by 2010. Area of temperate needle-leaved woodlands rose slowly from

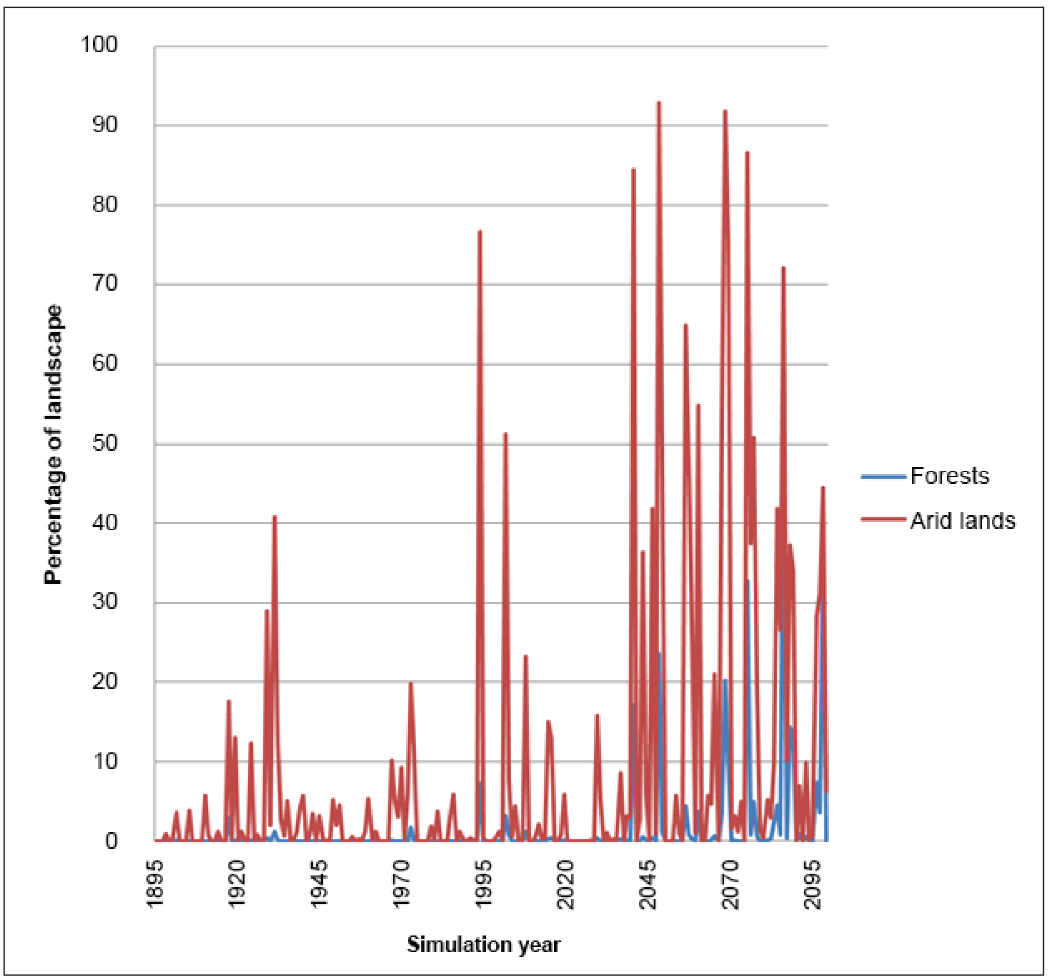

Figure 7.4—Simulated historical (1895–2008) and future (2009–2100) annual area burned as a proportion of the study area simulated by the MC1 model. Future projections used MIROC general circulation model climate information under the A2 emissions scenario.

about 5 percent to >25 percent from 2010 to 2100, but variation in simulated area also increased, especially in the last decade. Climatically suitable habitat for xeromorphic shrublands was absent until 2045, then rose slowly to nearly 20 percent of the landscape by 2100. Climatically suitable habitat for temperate grasslands varied from nearly zero to >10 percent over the 2010-2080 period, and then declined to almost zero. Climatically suitable habitat for warm-season grasslands was absent until 2080, and then never increased to more than 1 percent of the study area.

Our combined DGVM-STM indicated continued temperate needle-leaf forest dominance, though with increasing temporal variation in area.

Future Vegetation Conditions—State-and-Transition Model Simulation Results

Our combined DGVM-STM indicated continued temperate needle-leaf forest dominance, though with increasing temporal variation in area (fig. 7.5). Area of cool needle-leaf forests was relatively constant, at slightly over 10 percent of the landscape until 2085, and then dropped to <5 percent. Subalpine forests remained at about 2 percent of the study area for most of the simulation period, then declined. Area of temperate needle-leaf woodlands was generally steady at about 10 to 15 percent of the landscape, but temporal variation in simulated area increased, especially in the last 20 years. Area of temperate shrublands declined slowly to about 5 percent by 2040, then rose to vary around 15 percent of the landscape. Climatically suitable habitat for xeromorphic shrublands was absent until the last three decades, then increased to about 20 percent of the area. Climatically suitable habitat for temperate grasslands was nearly absent until 2040, rose sharply to vary between 1 and 6 percent of the landscape, and then declined to near zero by 2080. Warm-season grasslands were never present in any significant amount.

Discussion

Effects of Model Linkage

Future vegetation conditions projected by our climate-informed STM differed from those generated by MC1 alone. MC1 included basic ecosystem processes such as carbon sequestration, wildfire disturbance, and a biogeography rule-base defining PVCs based on climate and biomass thresholds. However, the combined DGVM-STM model also incorporated vegetation successional trends, lag times owing to fire-resistant species, and other local vegetation dynamics. The coupled MC1-STM model showed, for example, significantly less variation in the area of temperate needle-leaved forest, which corresponds to ponderosa pine forest in the study area, over the next century compared to MC1 alone. We suggest that including species resistance to disturbance and ecological constraints on climate-driven vegetation change dampens episodic shifts in vegetation conditions and results in greater vegetation resilience than a DGVM alone might indicate.

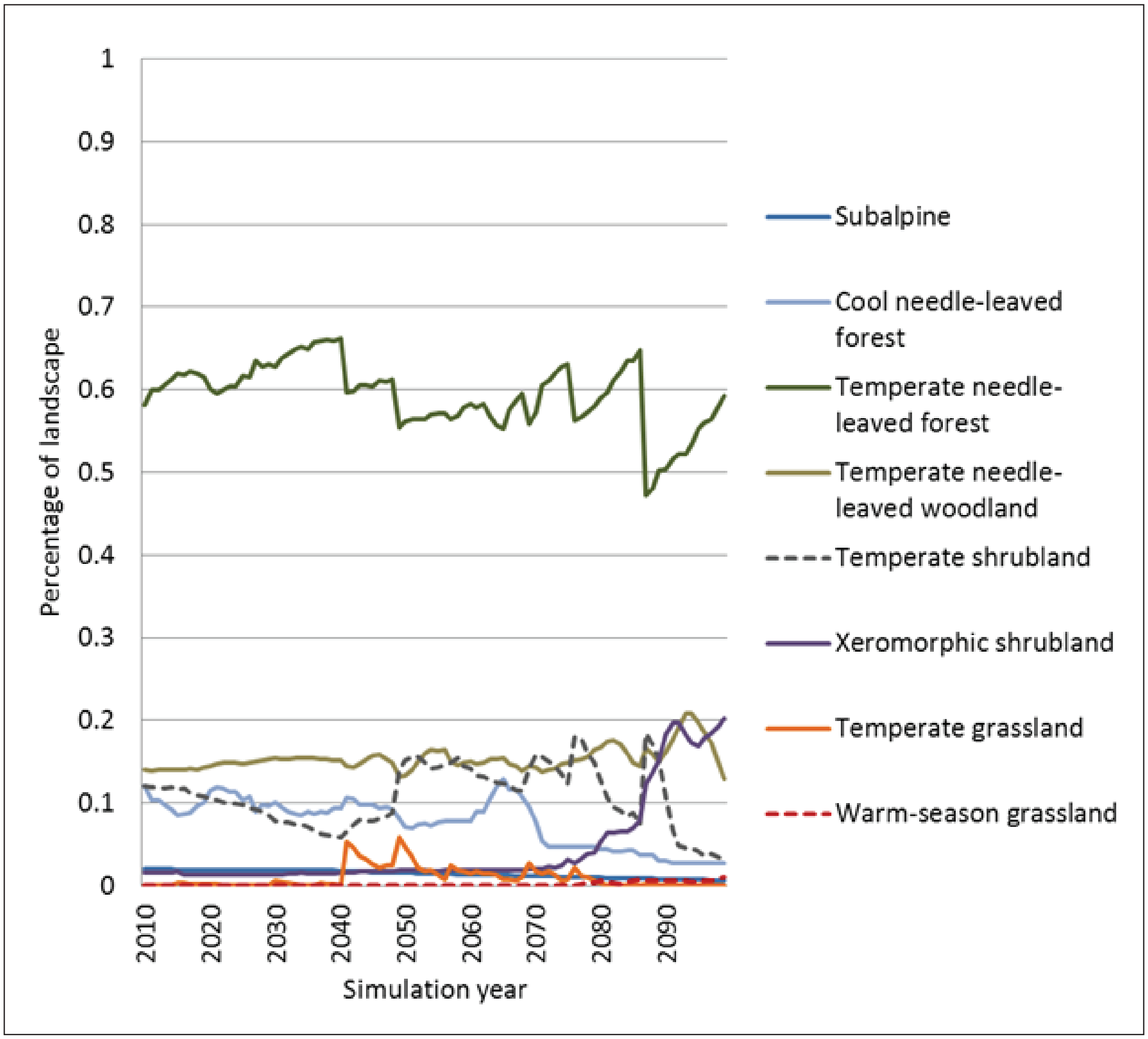

Figure 7.5—State-and-transition model simulation of potential future potential vegetation type trends using vegetation type trends from MC1 for MIROC general circulation model climate projections under the A2 emissions scenario.

The biogeography rule-base in MC1 estimates how changes in the carbon cycle can affect vegetation distribution given these future climate projections. For example, if the climate is generally cool and temperatures do not fluctuate widely seasonally, a given amount of carbon in a simulation pixel might be classified as cool needle-leaved forest. The same amount of carbon in a different climate zone that experiences warmer, drier summers might be called temperate needle-leaved forest. Although there is some lag built into MC1, PVCs can and do fluctuate sharply over relatively short timeframes as climate conditions change. The vegetation dynamics simulated by the model do not reflect a lag between changes in environmental conditions and the replacement of the current vegetation, especially when plant species are resistant to disturbance and long lived. Consequently, DGVM results should be used as a guide to what might happen if large-scale disturbances such as extensive insect outbreak, a stand-replacing fire, an extensive windthrow or heatwave mortality, wipe the landscape slate clean and facilitate quick replacement of plant communities. Even more importantly, DGVM results alone should not be associated with specific years, as natural climate variability is poorly represented by climate models in the future and decreases the temporal accuracy of climate trends in the future.

On the other hand, STMs simulate detailed vegetation dynamics, including growth, disturbance resistance, species competition and succession, natural disturbance and management impacts, and others, but have not traditionally allowed for changes in climate. Our results show that simulating detailed vegetation dynamics and including factors such as specific growth rates and resistances to disturbance, can produce decade- to century-long lags to climate change and associated disturbance impacts.

Woodlands, shrublands, and grasslands did not show the same level of resistance as dry forests to climate change in our coupled model simulations, largely because the species that comprise these communities in our study area are generally not as long lived or fire resistant as many of the early-seral forest tree species.

Woodlands, shrublands, and grasslands did not show the same level of resistance as dry forests to climate change in our coupled model simulations, largely because the species that comprise these communities in our study area are generally not as long lived or fire resistant as many of the early-seral forest tree species. Rather, the tree, shrub, and grass species that characterize arid-land communities are generally killed or top killed by fire, and then recolonize via sprouting, stored propagules, or dispersed propagules. Thus, when fire occurs in these communities, they often move to early-successional or open condition state classes, at which point available resources and lack of competition facilitate potential vegetation shifts. While the ponderosa pine forests in our area resisted change and dampened climate-induced fluctuations because of the fire resistance of mature ponderosa pine, the woodlands, shrublands, and grasslands all showed climate-mediated fluctuations over relatively short timeframes. Thus, we might expect similar landscapes dominated now and in the future by woodlands, shrublands, and grasslands to be less stable than dry forests in the face of climate variation.

Limitations

Our approach has several assumptions and limitations:

- We assume that wildfire suppression remains as effective in the future as it is now. However, extreme fire weather may become more frequent (Westerling et al. 2006), and thus fire frequency and fire size may increase more than our coupled model reflects.

- MC1 does not incorporate insect outbreaks. The STMs do incorporate insect outbreaks, but our approach assumes current roles and probabilities of insect outbreaks will be similar in the future. This may well not be the case. The severity and distribution of some recent insect outbreaks differ from what can be inferred from historical records, and higher temperatures associated with climate change are believed to be a significant factor in these differences (Aukema et al. 2008, Carroll et al. 2004, Logan and Powell 2001). For example, the large mountain pine beetle outbreak in British Columbia has expanded into northern areas and into areas east of the Rocky Mountains in Alberta, where mountain pine beetles were not successful in the past because of cold winter temperatures (Carroll et al. 2004). Our process could accommodate changes in insect or other disturbances if we included changing trends in future frequency and severity of insect outbreaks in our STMs.
- We did not build in lag times for species migration in the STMs. Paleoecological records indicate that migration rates for tree species are approximately 200 to 300 m/yr (Fischlin et al. 2007), but there is great uncertainty in that estimate, lags in response may vary considerably, and landscape fragmentation will also affect migration. All the PVCs projected to occur in the three climate scenarios examined in this study exist in or near to our study area at present, making incorporation of migration lags in our models less critical.
- We assume that the general dynamics of current vegetation and potential vegetation types adequately reflect similar vegetation conditions in the future under different climatic conditions, and that the types we chose to represent broader PVCs are indeed representative. Growth rates, succession, and other factors and interactions could change in the future, even in generally similar vegetation conditions. Past species response to changing climate observed in the paleoecological record shows that the abundance and distribution of plant species shift individualistically in response to climate fluctuations (Davis and Shaw 2001, Delcourt and Delcourt 1991, Whitlock 1992), leading to new species assemblages and communities. Increasing temperatures associated with climate change, and corresponding increases in summer drought stress and fire frequency in the Pacific Northwest, will probably lead to changing species distribution in the region, resulting in vegetation types different from those we see today (Zolbrod and Peterson 1999).

- Our MC1 simulations did not account for complex topography, owing to the scale of available climate projections, which may be important in mountainous regions such as that of our study area.
- Our coupled model results should not be associated with specific years, as natural climate variability is poorly represented by climate models in the future. Rather, our projections should be considered as potential trends across many years to decades.

Despite these limitations, the results of our coupled model exercise can help in understanding potential interactions between coarse-scale vegetation processes and finer scale vegetation dynamics in a changing climate.

Conclusions

Our modeling process links a DGVM to STMs to localize potential climate change effects on vegetation. With this linkage, we used information from climate-vegetation-disturbance interactions in DGVM simulations and used it to inform vegetation change and fire parameters in local STMs, which model finer scale vegetation dynamics. The addition of finer scale vegetation dynamics resulted in lags in climate effects and increased vegetation resilience to climate change than what was indicated by DGVM output alone.

Managers and others can use our process to better understand potential climate-induced shifts in local vegetation, and through linkage with other ILAP information, fuel conditions, potential wildlife habitats, biomass, silvicultural treatment economics, and other important vegetation-related trends and values. Managers wishing to retain moist forests with large, old trees, for example, could examine the various kinds of stand management activities (thinnings from below, fuel treatments, prescribed fire, no vegetation treatment, and others) included in our STMs and determine what set of treatments results in the conservation of moist forests across all three climate scenarios. Expanding this work to other areas could help natural resource planners and others more easily incorporate climate change into their decisionmaking process.

Managers and others can use our process to better understand potential climate-induced shifts in local vegetation, and through linkage with other ILAP information, fuel conditions, potential wildlife habitats, biomass, silvicultural treatment economics, and other important vegetation-related trends and values.

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English Equivalents

When you know:	Multiply by:	To find:
Millimeters (mm)	0.03934	Inches
Centimeters (cm)	0.394	Inches
Meters (m)	3.28	Feet
Meters per second (m/s)	2.24	Miles per hour
Kilometers (km)	0.621	Miles
Hectares (ha)	2.47	Acres
Cubic meters (m^3)	35.3	Cubic feet
Tonnes (t)	1.102	Tons
Kilojoules per square meter (kJ/m^2)	0.08806	British thermal units per square foot
Degrees Celsius	1.8 °C + 32	Degrees Fahrenheit